

FINAL TECHNICAL REPORT FOR

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MECHANISMS IN CLIMATE INFLUENCES AND
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Applications of Principled Search Methods in Climate Influences and Mechanisms

Statistical Forecasts of Wildfire

Introduction

Forest and grass fires cause economic losses in the billions of dollars in the U.S. alone [14]. In addition, boreal forests constitute a large carbon store; it has been estimated that, were no burning to occur, an additional 7 gigatons of carbon would be sequestered in boreal soils each century [10]. Effective wildfire suppression requires anticipation of locales and times for which wildfire is most probable, preferably with a two to four week forecast [13], so that limited resources can be efficiently deployed. The United States Forest Service (USFS), and other experts and agencies have developed several measures of fire risk combining physical principles and expert judgment [11, 12], and have used them in automated procedures for forecasting fire risk. Forecasting accuracies for some fire risk indices in combination with climate and other variables have been estimated for specific locations [1,8], with the value of fire risk index variables assessed by their statistical significance in regressions. In other cases, the MAPSS forecasts [23, 24] for example, forecasting accuracy has been estimated only by simulated data.

We describe alternative forecasting methods that predict fire probability by locale and time using statistical or machine learning procedures trained on historical data, and we give comparative assessments of their forecasting accuracy for one fire season year, April-October, 2003, for all U.S. Forest Service lands. Aside from providing an accuracy baseline for other forecasting methods, the results illustrate the interdependence between the statistical significance of prediction variables and the forecasting method used.

Data

The Terrestrial Observation and Prediction System (TOPS) [5,6] provides measures of

the following variables for years 2000-2003 for the lower 48 states gridded to 8km (approximately 15,814 acres) resolution using a Lambert equal-area projection (Figure 1 and Figure 2):

FPAR (Fraction of Photosynthetically Active Radiation absorbed by vegetation)

LAI (Leaf Area Index)

TMIN (Minimum temperature over past 24 hours)

TMAX (Maximum temperature over past 24 hours)

PRECIP (Amount of precipitation, rain or snow, over past 24 hours)

VPD (Vapor Pressure Deficit; an inverse function of humidity)

FPAR and LAI measures are collected every 8 days from NASA MODIS satellites [15]. The remaining variables are produced daily from ground observations collected by the National Climate Data Center (NCDC).

Fire forecasting models have been designed to predict number of fire days [1], or probability of at least one fire [8], or burned area [7], or fire “risk,” the last a quantity that is not independently measurable and hence not amenable to an assessment of forecast accuracy. We estimate the probability of at least one fire in any 30 day period in the fire season within a 64 square kilometer grid cell. The National Interagency Fire Management Integrated Database (NIFMID) provides records of fires occurring on USFS land that required suppressive action for the years 1986-2003 [4], including fire location, ignition date and final fire size. In nearly all cases (99.9%), a fire lies entirely within the boundary of a single grid cell.

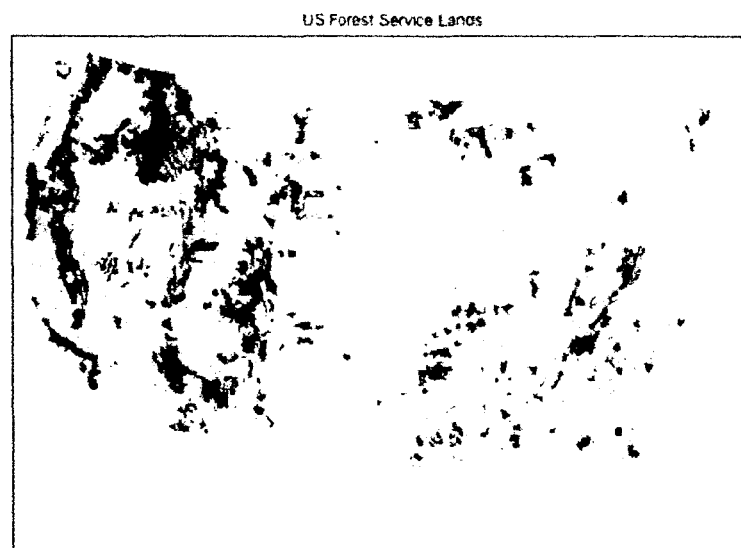


Figure 1: U.S. Forest Service Land

The USFS currently uses a map of fuel types (See Figure 2 and Table 1) in their wildfire assessment system [3,16] gridded to 1 km resolution.

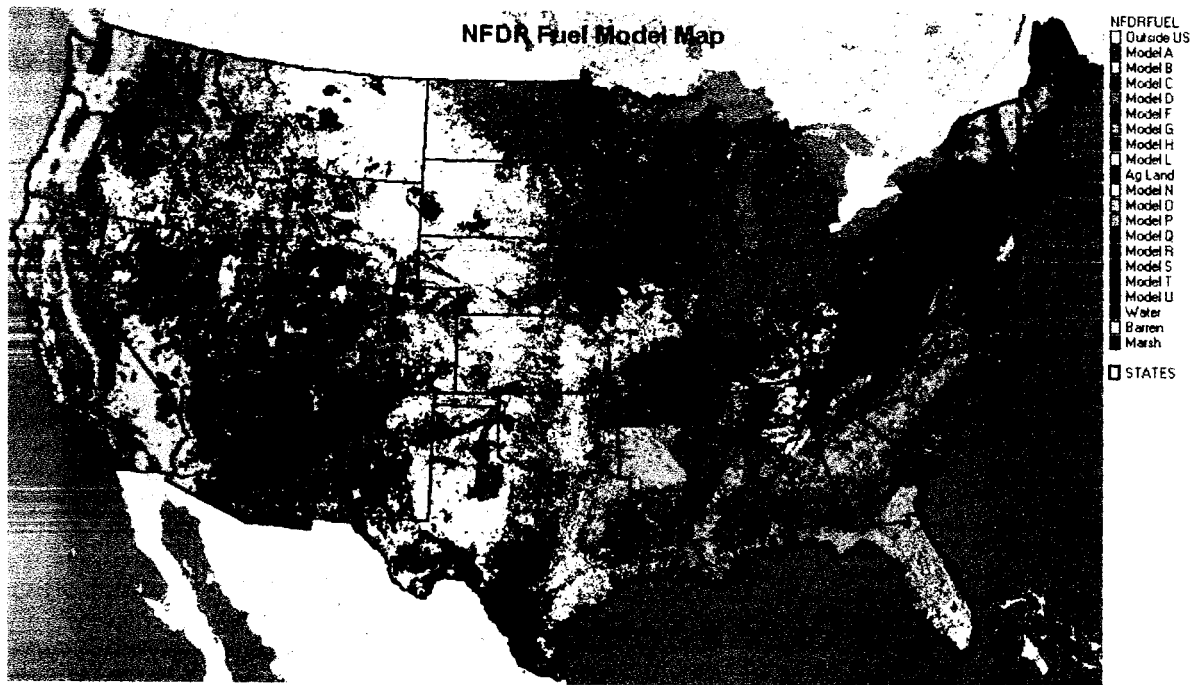


Figure 2

| Code | #Cells | #USFS Cells | Description |
|------|--------|-------------|---|
| A | 615 | 21 | Western Annual Grass |
| B | 547 | 166 | California Mixed Chaparral |
| C | 7462 | 2938 | Pine Grass Savanna |
| D | 2024 | 105 | Southern Rough |
| F | 4370 | 944 | Intermediate Brush |
| G | 7805 | 4164 | Short Needle Conifers with Heavy Dead Load |
| H | 2602 | 1934 | Short Needle Conifers with Normal Dead Load |
| L | 21456 | 1593 | Western Perennial Grasses |
| M | 27233 | 843 | Agricultural Land |
| N | 450 | 7 | Sawgrass or Other Thick Stemmed Grasses |
| O | 930 | 158 | High Pocosin |
| P | 5892 | 716 | Southern Pine Plantation |
| Q | 623 | 33 | Alaskan Black Spruce |
| R | 19459 | 2312 | Hardwoods |
| S | 163 | 110 | Alpine Tundra |
| T | 15155 | 1833 | Sagebrush-Grass Mixture |
| U | 365 | 2 | Western Long-Needle Conifer |
| V | 861 | 13 | Water |
| W | 2995 | 75 | Barren |
| X | 69 | 1 | Marsh |

Table 1

For each year Y in 2000-2003, and each day-of-year T in 1-365 (except 2000, which begins on day-of-year 65), and each 64 sq. km. grid cell, values for the following variables were assigned:

- FPAR on day T, year Y
- LAI on day T, year Y
- TMIN on day T, year Y
- TMAX on day T, year Y
- PRECIP on day T, year Y
- VPD on day T, year Y
- TMIN averaged over [T-1,T-7], year Y
- TMAX averaged over [T-1,T-7], year Y
- PRECIP averaged over [T-1,T-7], year Y
- VPD averaged over [T-1,T-7], year Y
- TMIN averaged over [T-1,T-30], year Y
- TMAX averaged over [T-1,T-30], year Y
- PRECIP averaged over [T-1,T-30], year Y
- VPD averaged over [T-1,T-30], year Y
- Number of fires in calendar year Y-1
- Number of fires in calendar years [Y-2, Y-15]

All variables were standardized to zero mean and unit variance.

A Thermal Anomaly MODIS product is available which, if used in place of U.S. Forest Service fire records, would allow forecasting for the entire United State. The Thermal Anomaly product is very recent, however, and would not provide a substitute for number of fires years in calendar years, Y-2, Y – 15, a variable that proved to be significant.

Classifiers and Training

Three algorithms were trained: logistic regression [9], classification and regression trees [25], and support vector machines [22] with a radial basis kernel. All programs were coded using MATLAB libraries REF. In each case, training was with the 2000–2002 measures above. Logistic regression parameters were obtained with the Matlab Statistics Toolbox implementation, which performs 100 iterations of conjugate gradient search. Classification and regression parameters were obtained with the Matlab Statistics Toolbox implementation using the Gini measure and ten-fold cross-validation over ROC curve areas was used to prune the tree. Support vector machine tuning used default settings for LIBSVM 2.8. Supervision targets were scored as 1 if fire occurred within the succeeding 30 days, and 0 otherwise. Separate models from each classifier were trained for each month (e.g., March, April, May, ...) and for each fuel code. It is useful to know if recent weather events are on average important to forecast accuracy, or, alternatively, if the burn history for a place and day of year are accurate for a succeeding year. Accordingly, we also produced models that used burn history variables only as inputs.

Testing Method

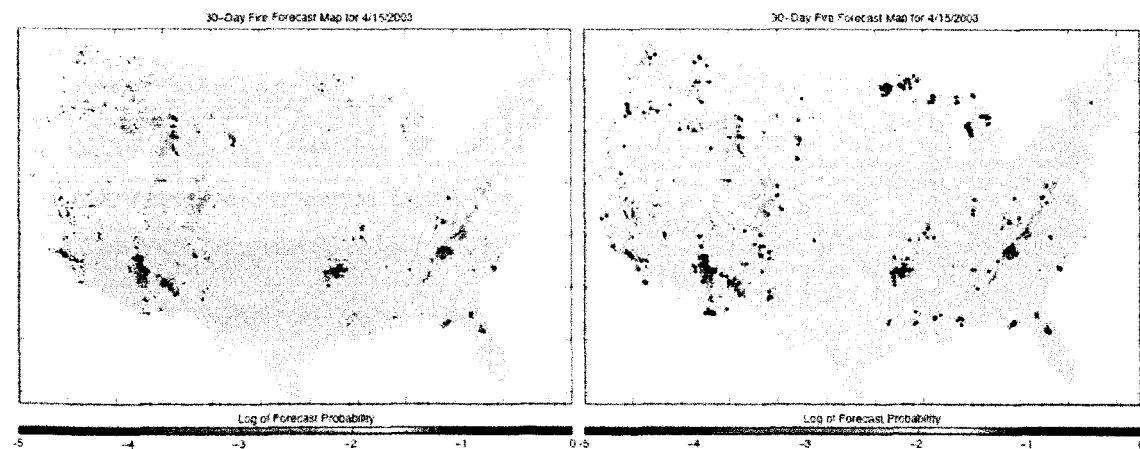
Each classifier was used to assign a fire occurrence probability to each grid cell in USFS

lands for the 30-day period following the 15th day of each month from March through October of 2003. The NIFMID data for 2003 were then used to obtain ROC (Receiver Operating Characteristic) curves [18] for each fuel code, month and forecasting method. Areas under ROC curves (AUC) were calculated for each case. Maps of the resulting probabilities produced by one of the algorithms (logistic regression), and the actual fire occurrences, for April and July of 2003, are shown in Figure 3.

Results

The ROC curves for all forecasting methods, fuel codes and months for which at least 10 fires occur are shown in Appendix 1. Area under the curve (AUC) and number of acres burned are given in the legend for each figure. Tables 1-3 in Appendix 2 compare AUC values, fuel code by fuel code, with (top value) and without (bottom value) climate variables, for each of the 3 forecasting methods. Empty cells are for fuelcode months with fewer than 10 fires. Fuelcodes omitted altogether had fewer than 10 fires in any month. Cells where the AUC values differ significantly ($p < 0.05$ for a two-sided test) are highlighted in green, using Hanley's test [17, 18].

Tables 4-6 report all pairwise comparisons of the three classifier methods for each fuelcode month using both climate and burn history variables. Again, cells are left blank for fuelcode-months fewer than 10 fires. Cells are highlighted green if the first method significantly outperforms the second method, and they are highlighted magenta if the second method significantly outperforms the first. The same test and criterion for significance were used in these tables as those in Tables 1-3.



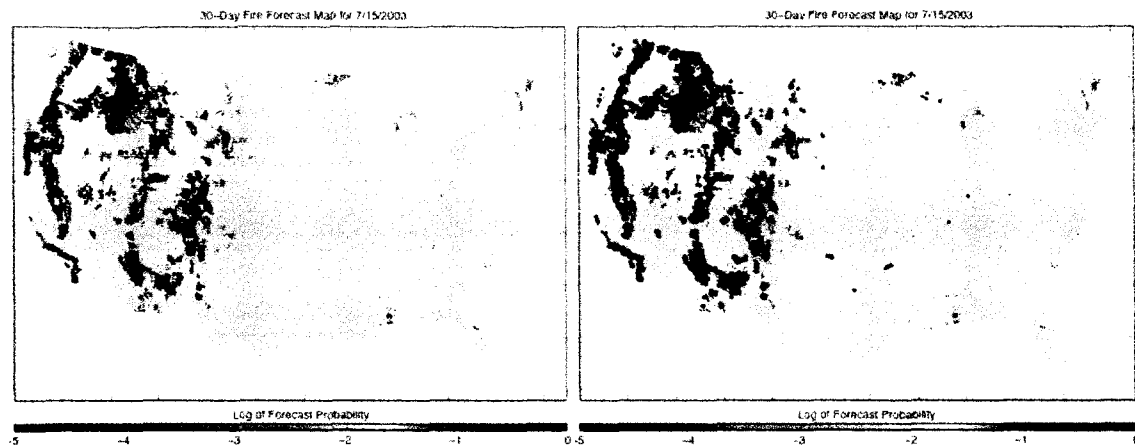


Figure 3

Discussion

The forecasting models tend to differ significantly in fuelcode-months with many fires. While climate variables are significant when support vector machine and CART classifiers are used, those variables are not significant when forecasting is with logistic regression, and on the whole, classification with logistic regression is substantially more accurate. Place is an effective proxy for many climate variables, and it may be that when associations of burn history and place are optimally exploited, on average climate variables are nearly independent of wildfire occurrence.

Several alternative explanations of our results are possible, but establishing any of them would require further extensive studies. The fire data we used in our study covers about 10% of the area of the lower 48 states, and different results might be obtained with fire data from a larger area; the MODIS Thermal Anomalies product is one possibility, although some problems with validation have been reported [19, 20]. Again, the value of climate variables for fire forecasts might be found in other studies, perhaps using other outcome criteria, such as acres burned or number of fire days rather than occurrence of at least one fire, but our results argue that such studies should consider multiple classification methods.

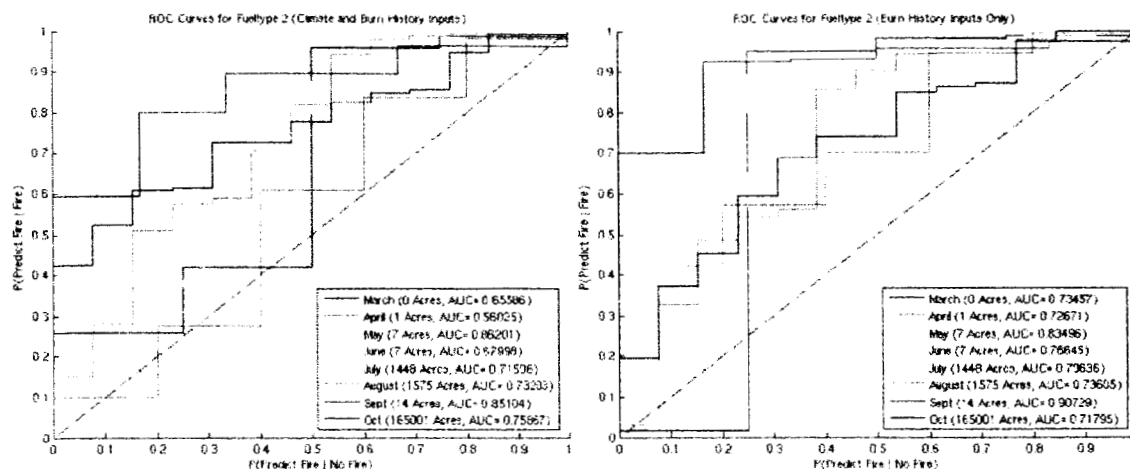
Except for precipitation, MODIS products that might serve in place of TOPS ground measured variables are presently available. Should the sufficiency of burn history for wildfire forecasting A MODIS burn product is recently available REF, which, over time, may permit global wildfire forecasting from burn history Model training on a planetary scale is confounded by agricultural burnings, but these are typically either small fires or, when large, fires of known origin. With parallelization, and appropriate data, wildfire forecasts for all boreal forests, or for the entire Earth landmass, are computationally feasible.

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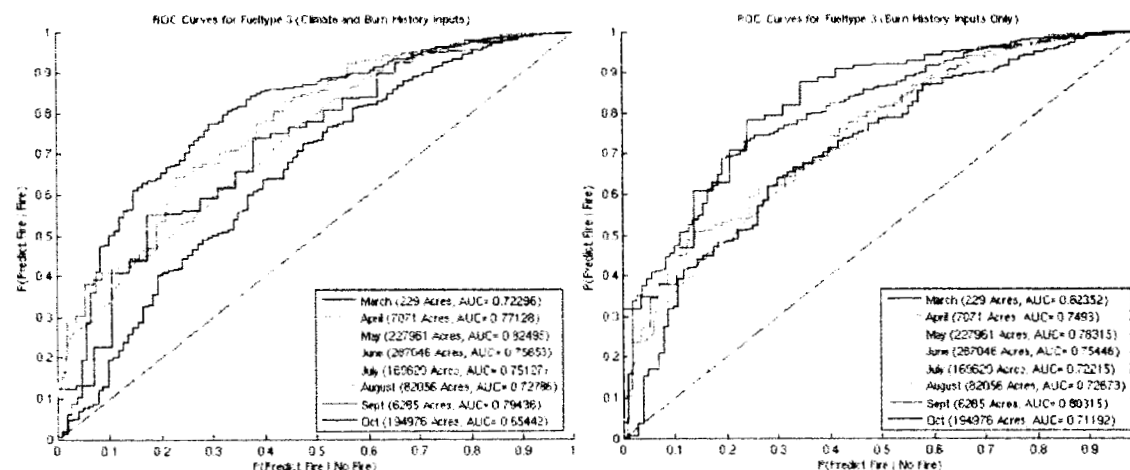
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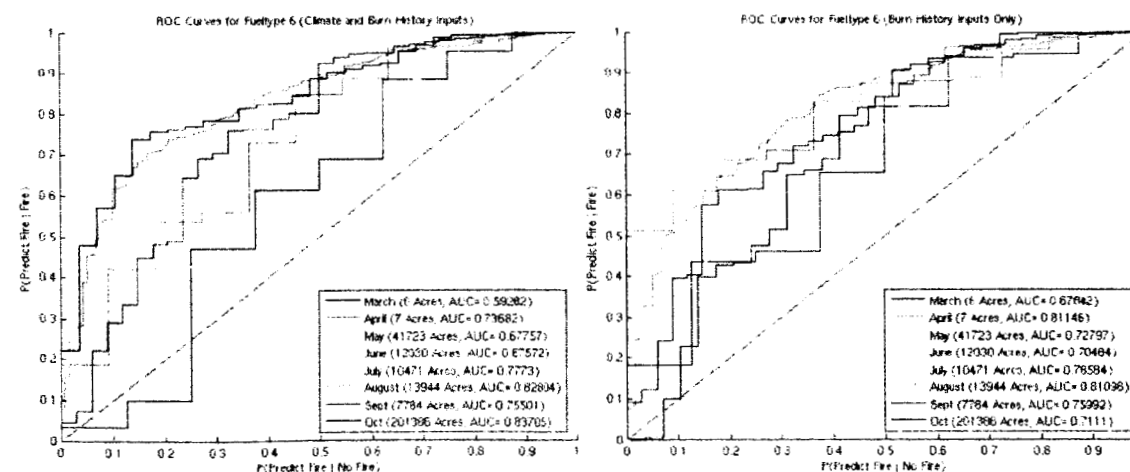
Appendix 1: ROC curves



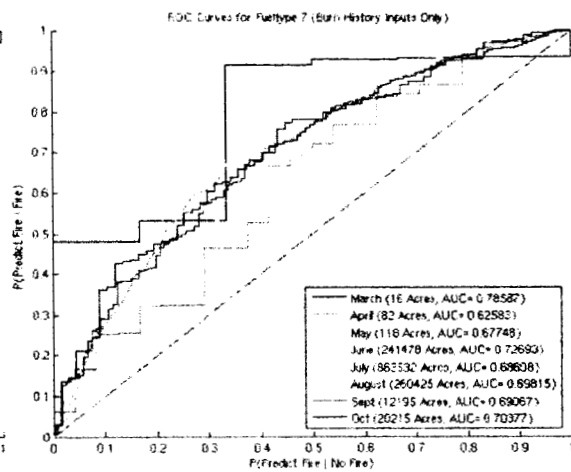
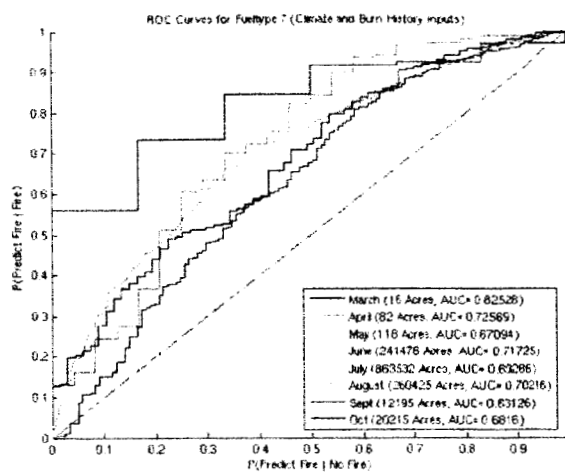
Fuel Code B: California Mixed Chaparral (logit method)



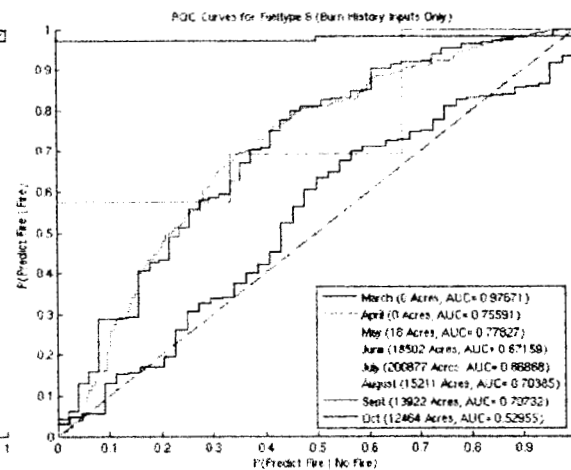
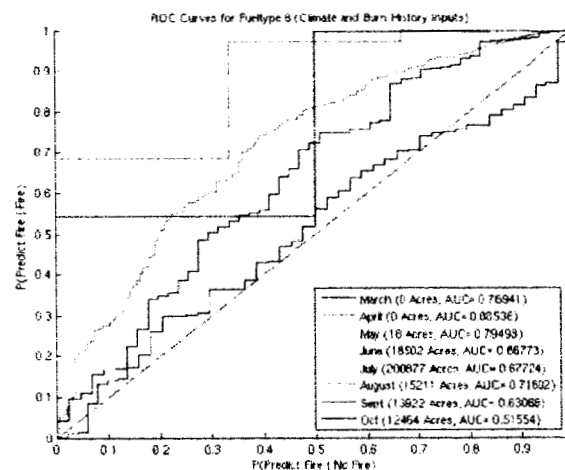
Fuel Code C: Pine Grass Savanna (logit method)



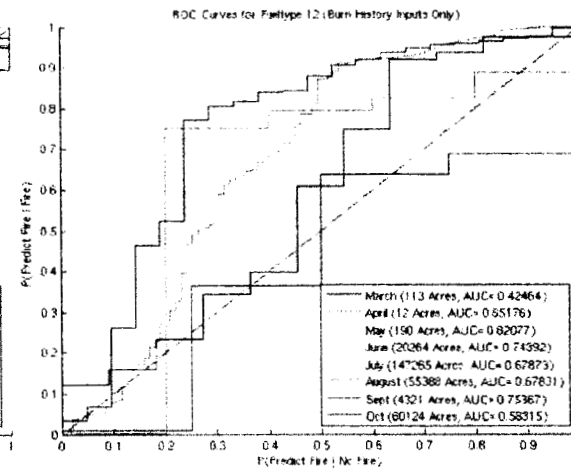
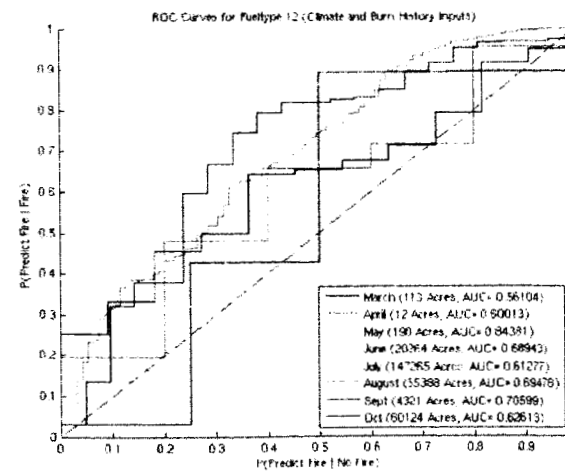
Fuel Code F: Intermediate Brush (logit method)



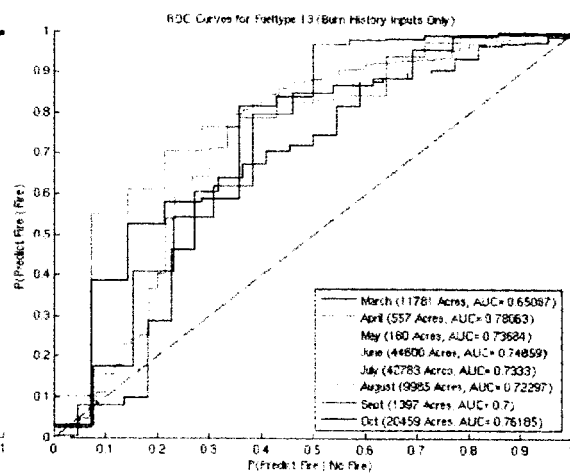
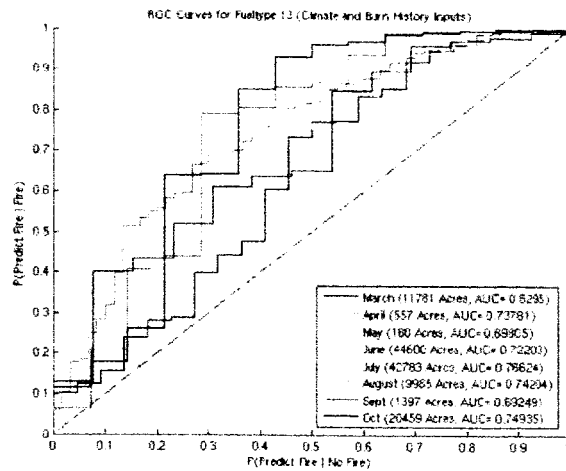
Fuel Code G: Short Needle Conifers, Heavy Dead Load (logit method)



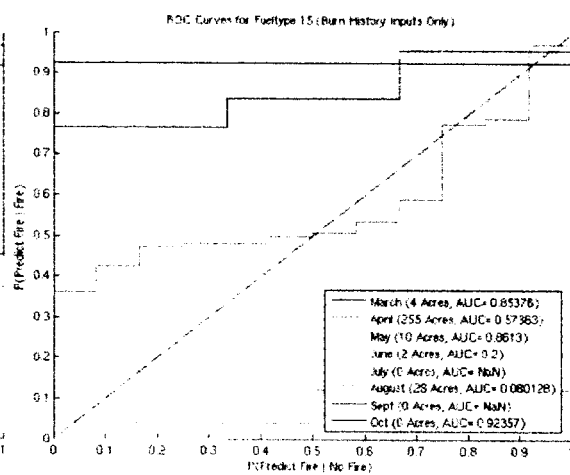
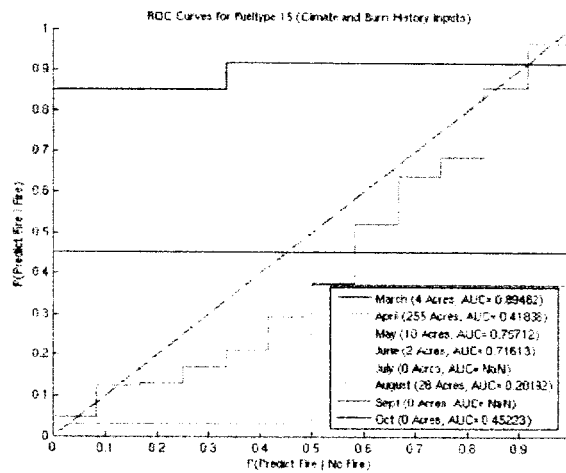
Fuel Code H: Short Needle Conifers, Normal Dead Load (logit method)



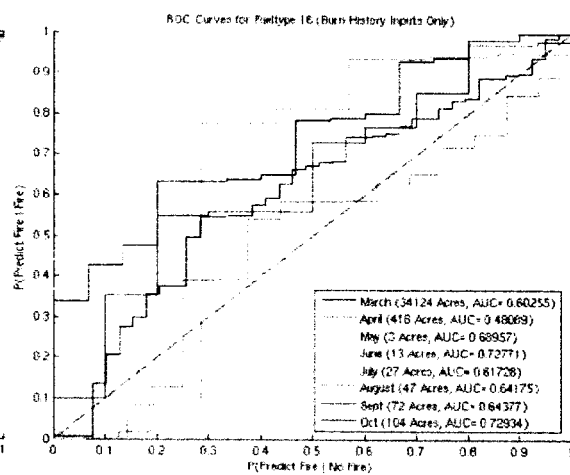
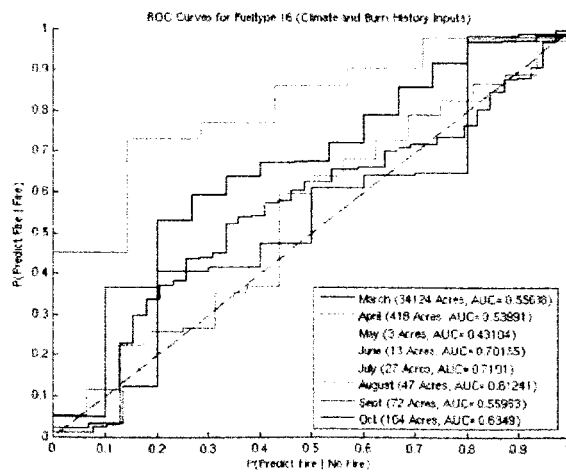
Fuel Code L: Western Perennial Grass (logit method)



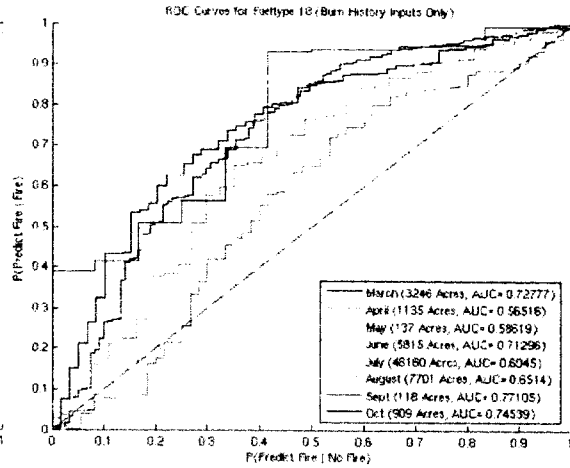
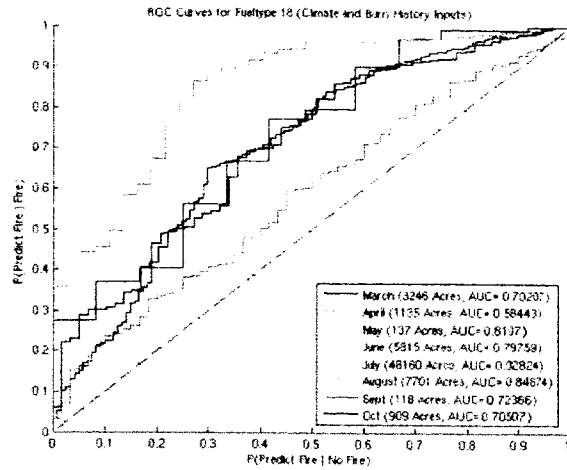
Fuel Code M: Agricultural Land (logit method)



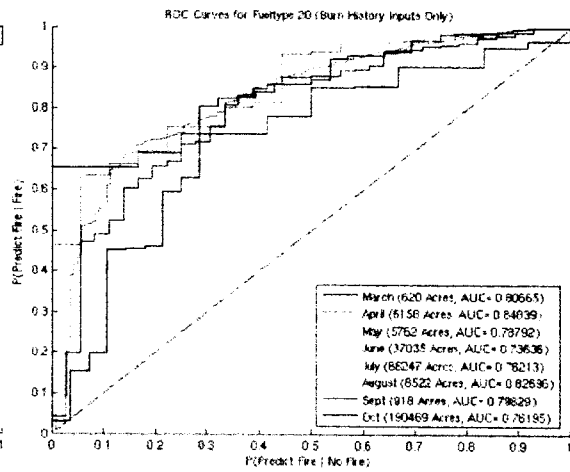
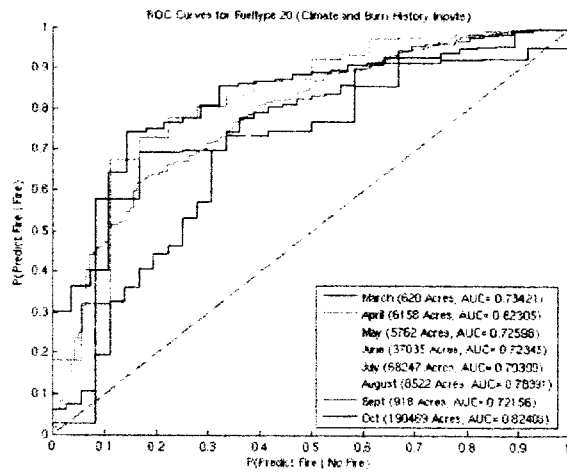
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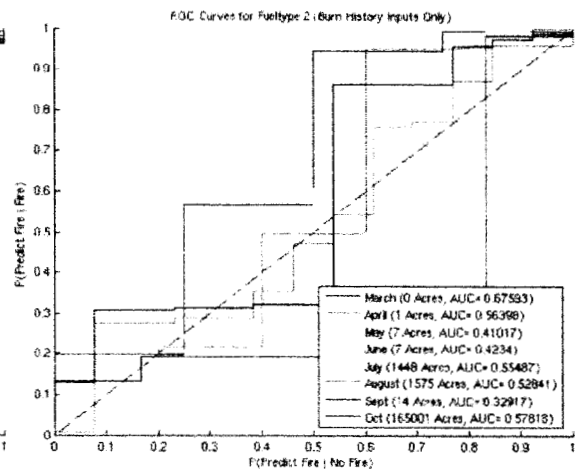
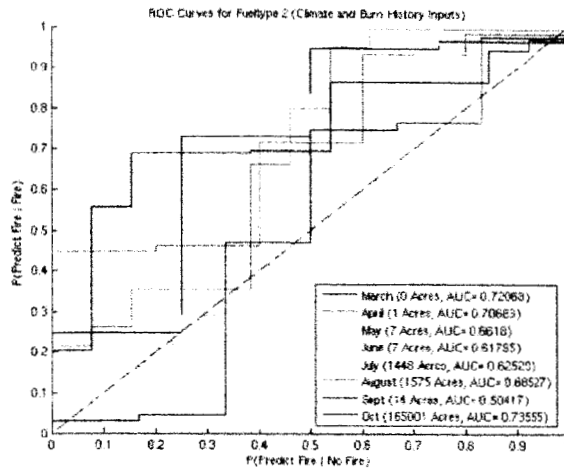
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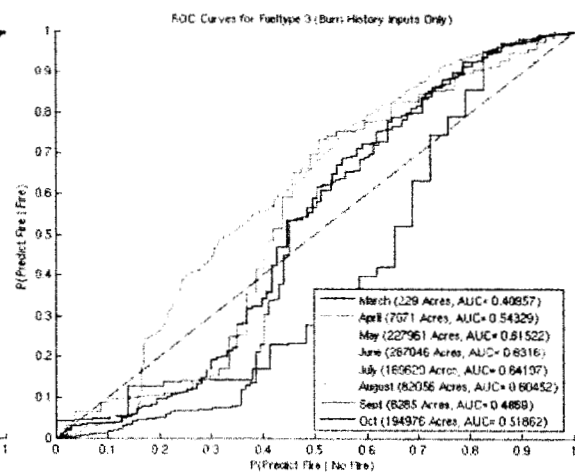
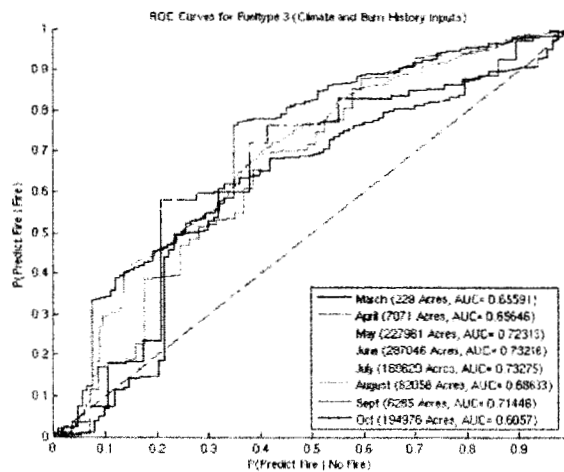
Fuel Code R: Hardwoods (logit method)



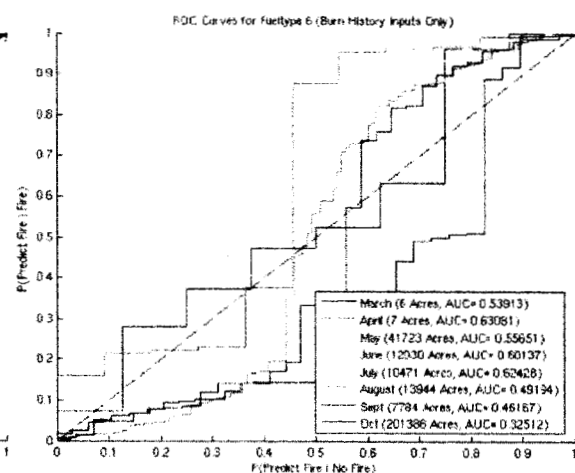
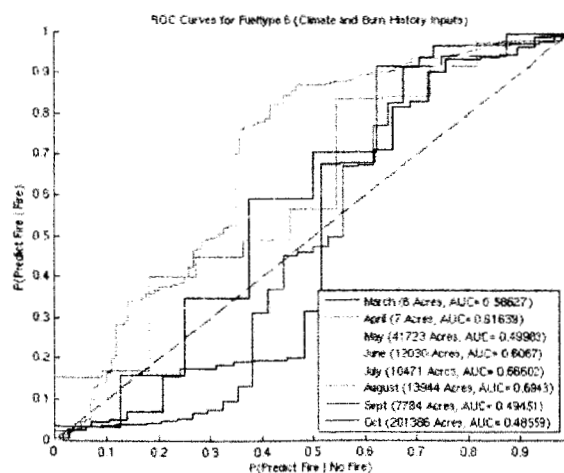
Fuel Code T: Sagebrush-Grass Mixture (logit method)



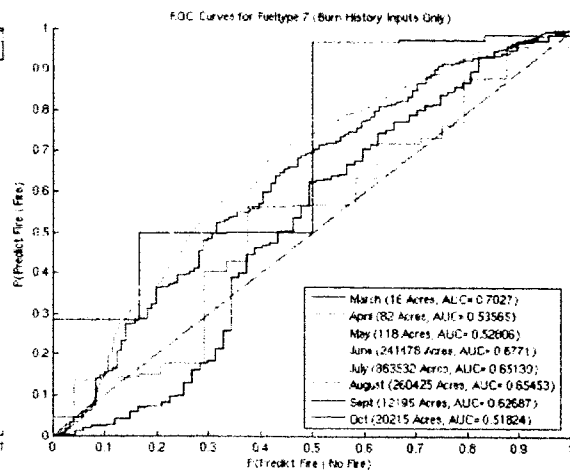
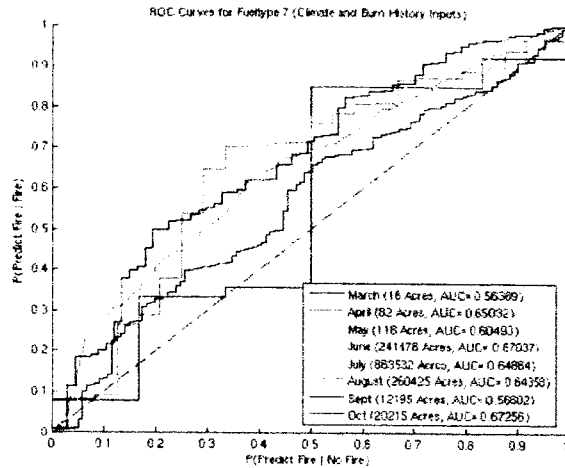
Fuel Code B: California Mixed Chaparral (CART method)



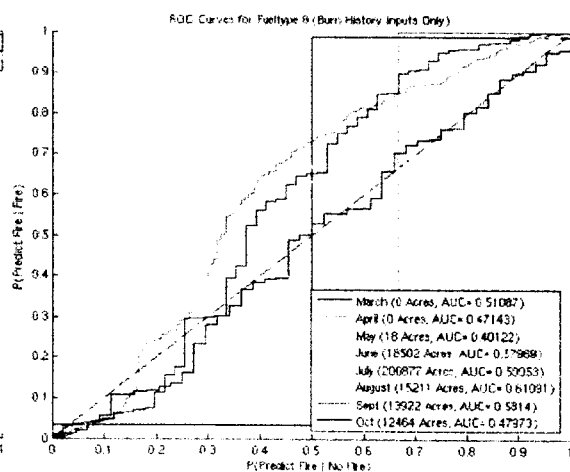
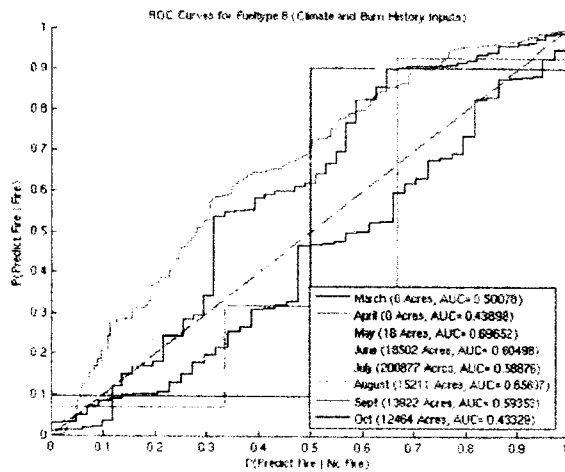
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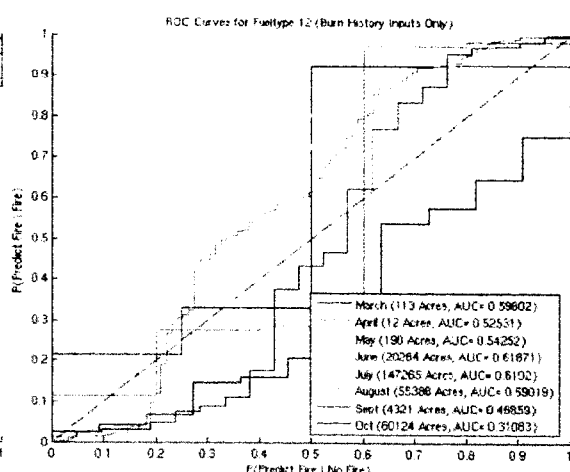
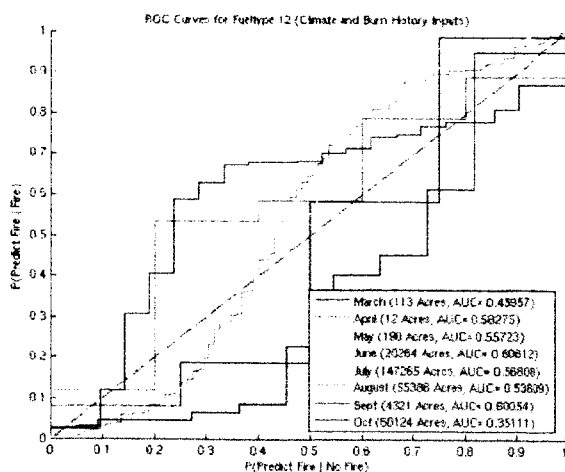
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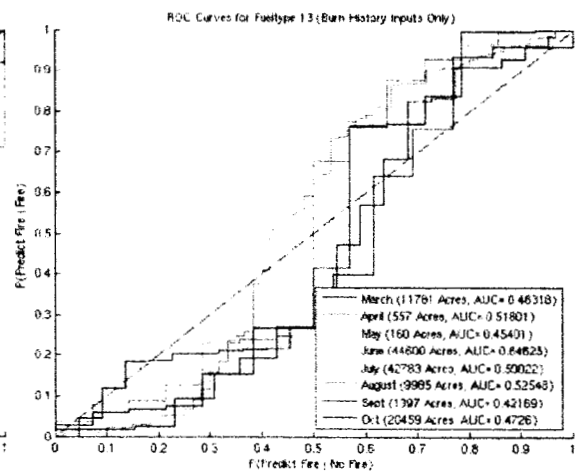
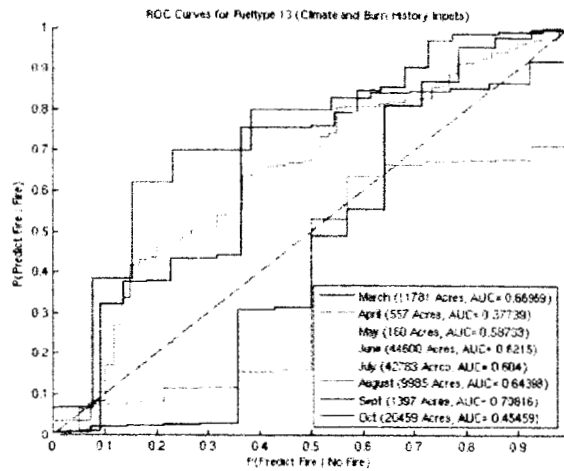
Fuel Code G: Short Needle Conifers, Heavy Dead Load (CART method)



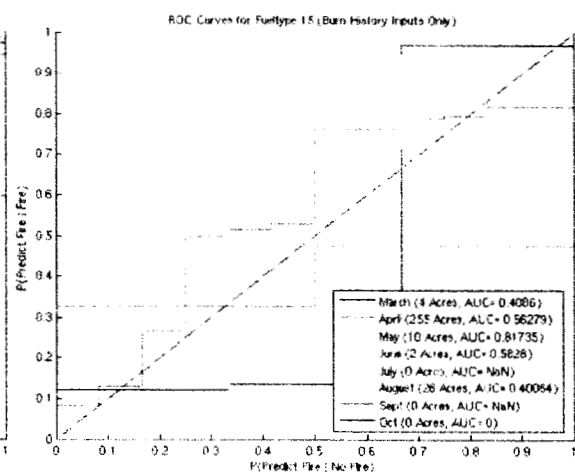
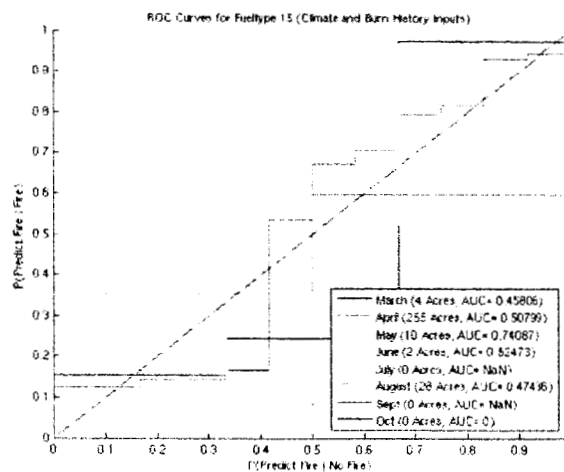
Fuel Code H: Short Needle Conifers, Normal Dead Load (CART method)



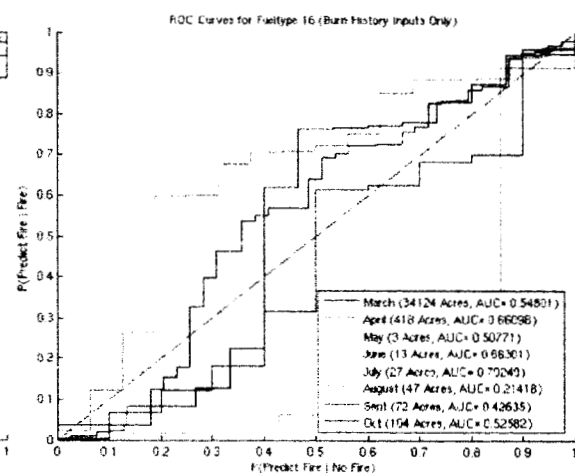
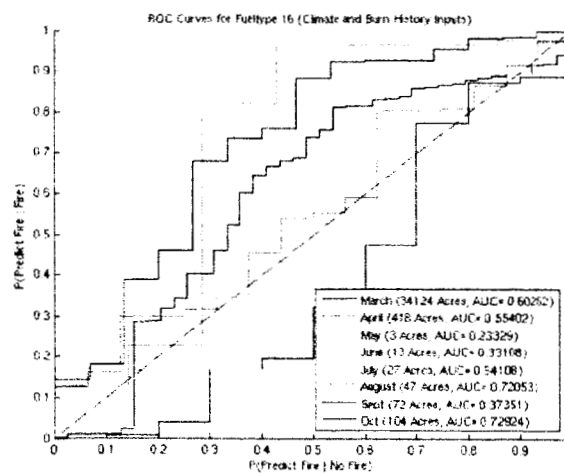
Fuel Code L: Western Perennial Grass (CART method)



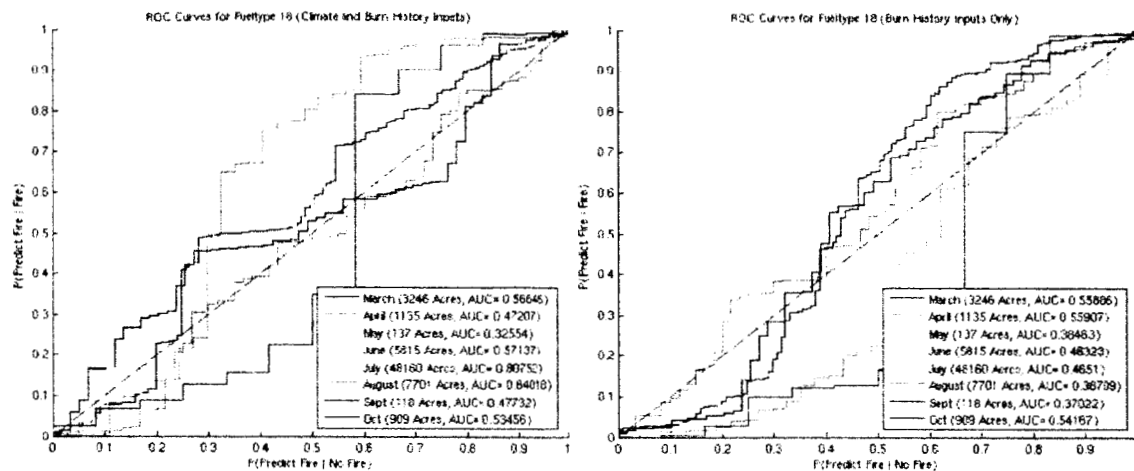
Fuel Code M: Agricultural Land (CART method)



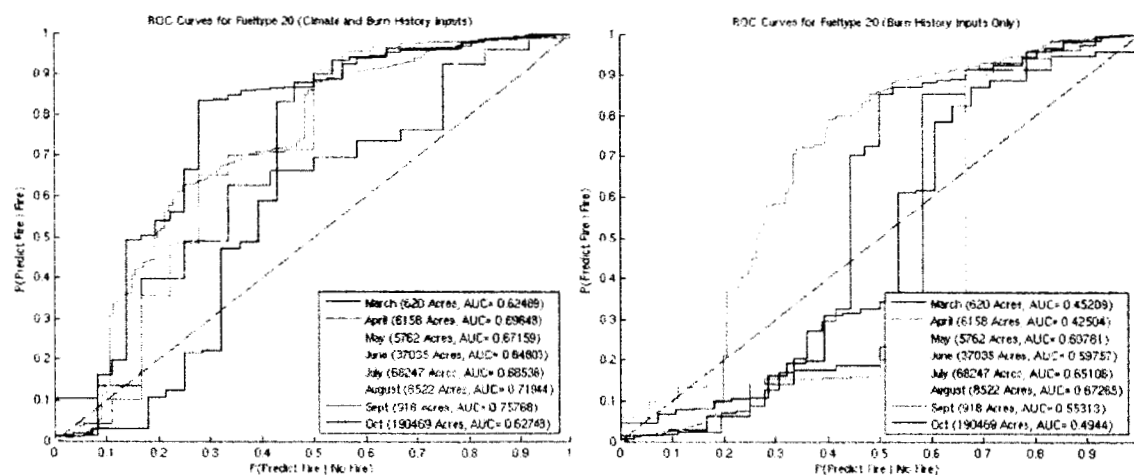
Fuel Code O: High Pocosin (CART method)



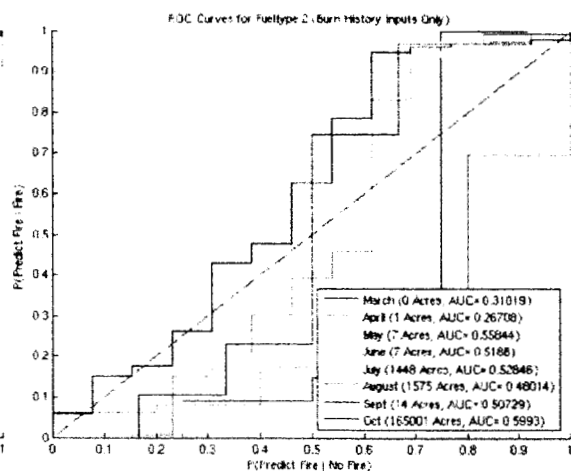
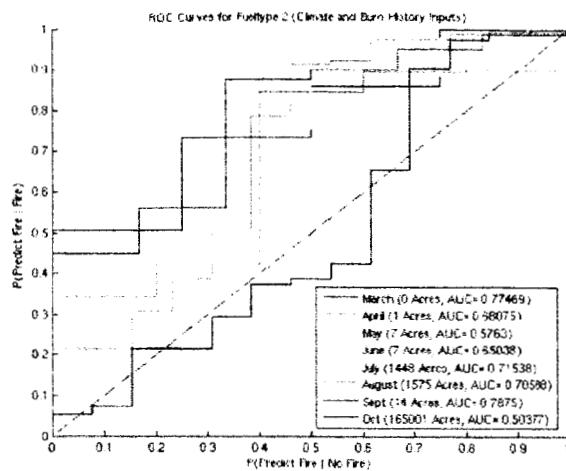
Fuel Code P: Southern Pine Plantation (CART method)



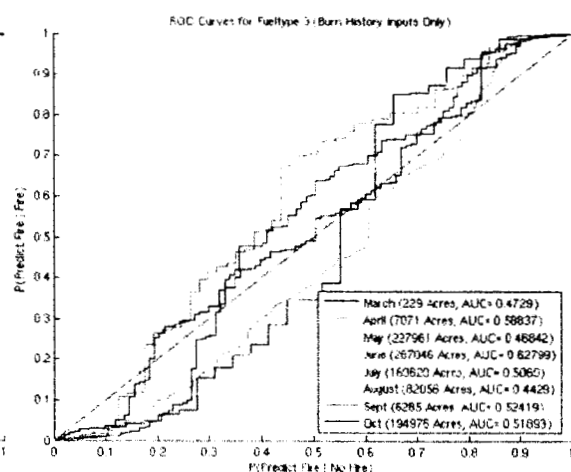
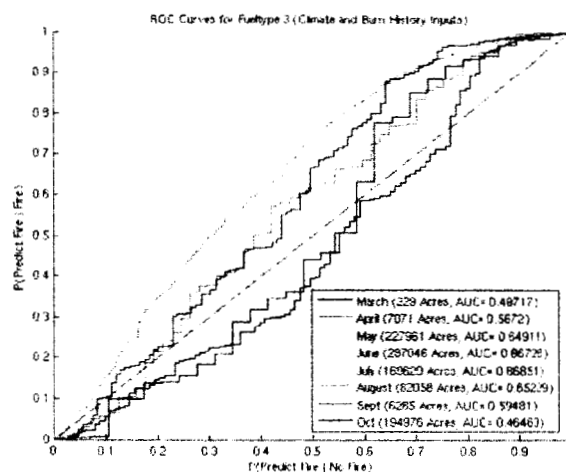
Fuel Code R: Hardwoods (CART method)



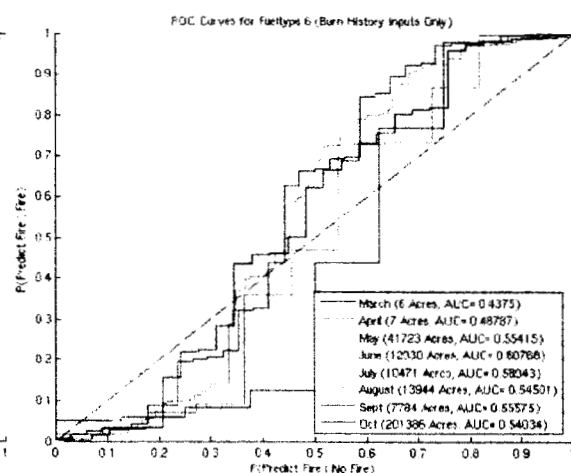
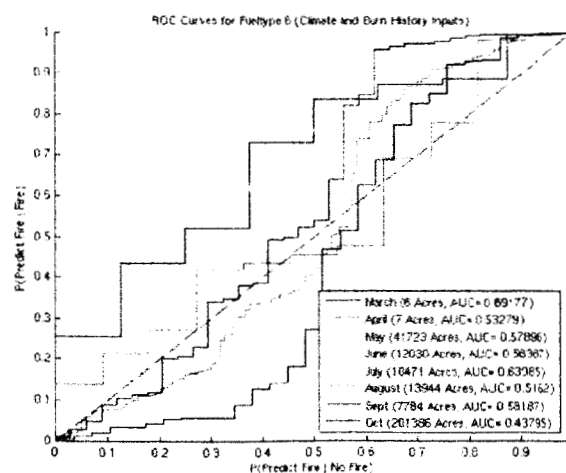
Fuel Code T: Sagebrush-Grass Mixture (CART method)



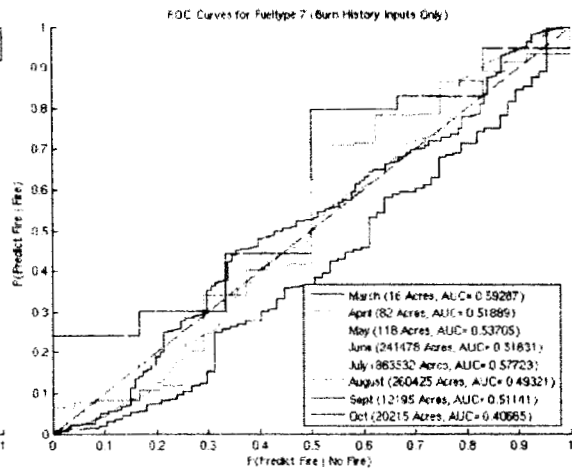
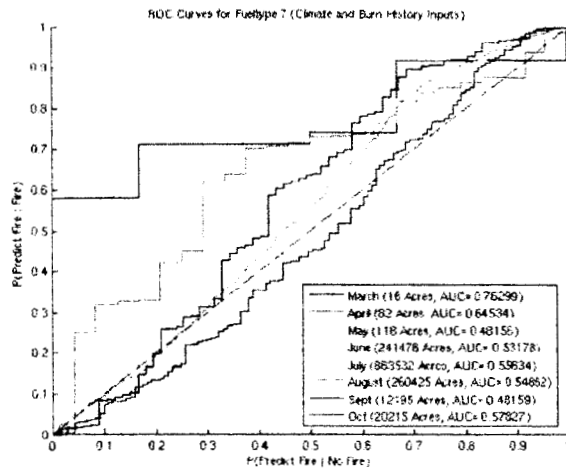
Fuel Code B: California Mixed Chaparral (SVM method)



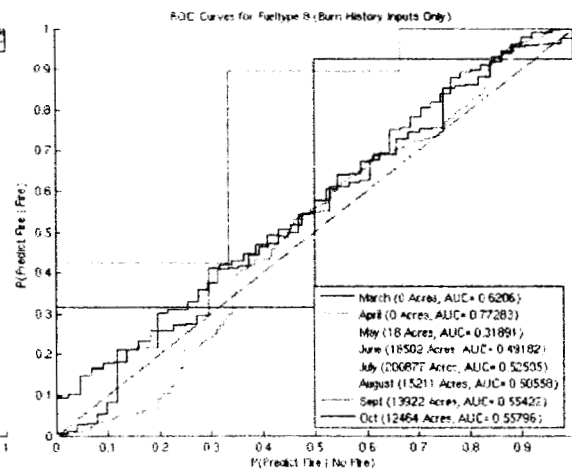
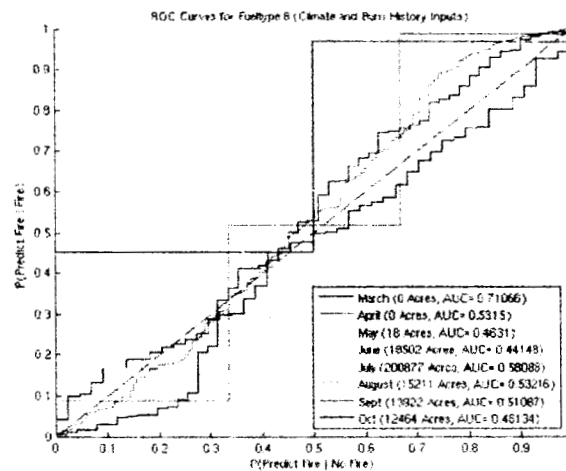
Fuel Code C: Pine Grass Savanna (SVM method)



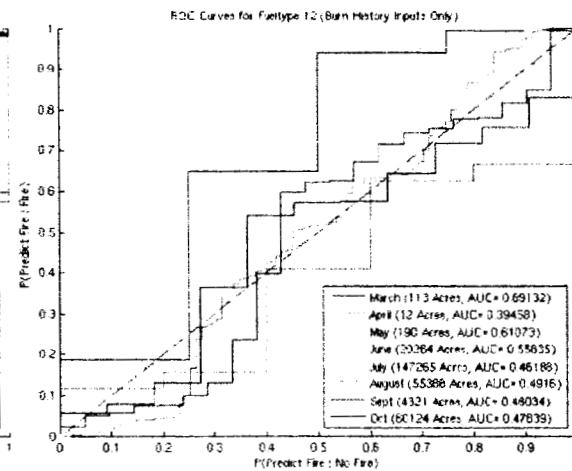
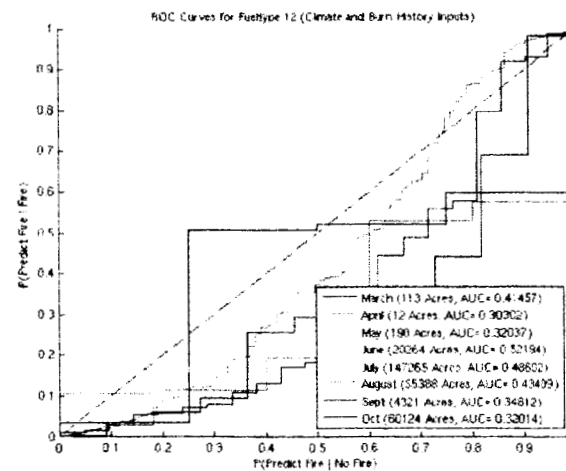
Fuel Code F: Intermediate Brush (SVM method)



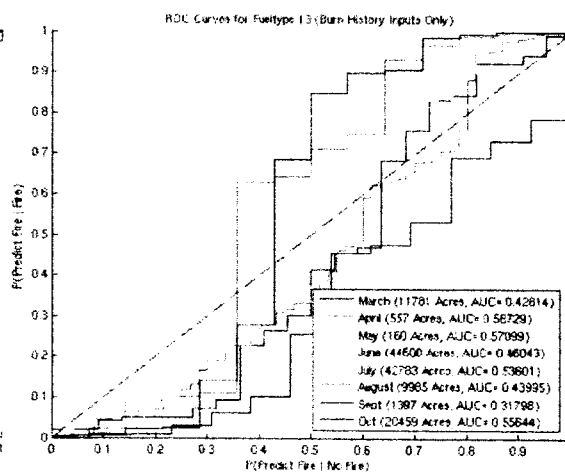
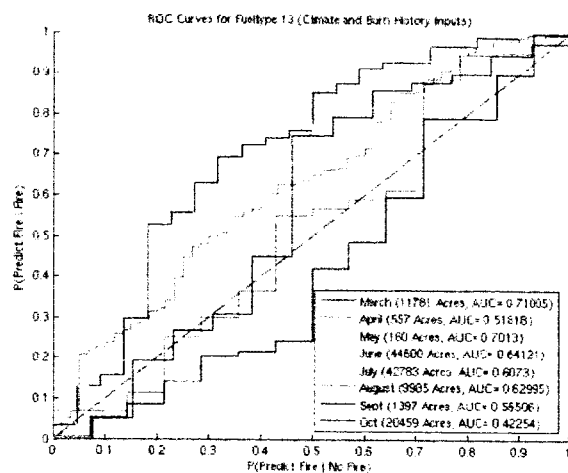
Fuel Code G: Short Needle Conifers, Heavy Dead Load (SVM method)



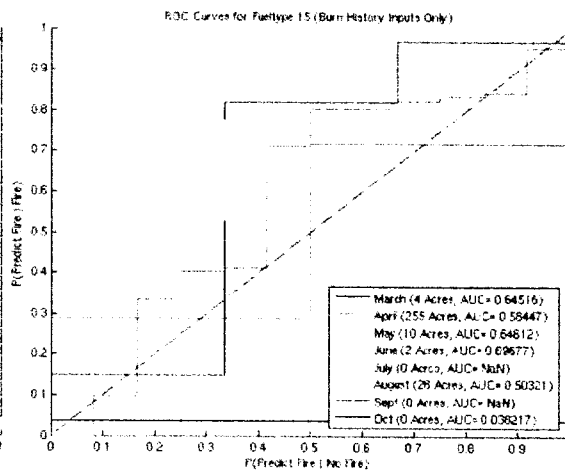
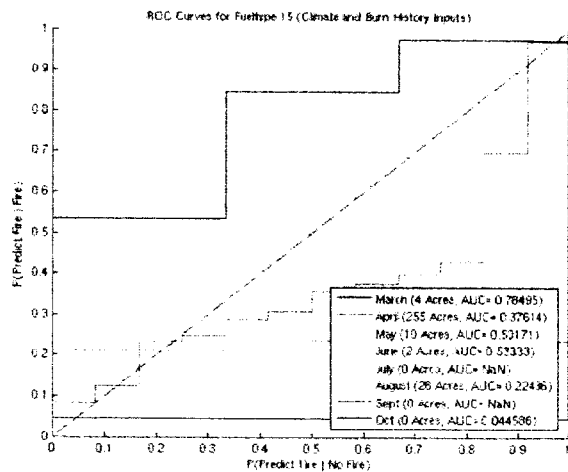
Fuel Code H: Short Needle Conifers, Normal Dead Load (SVM method)



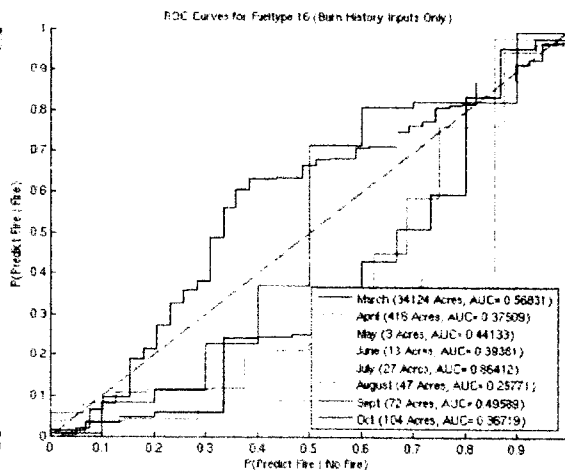
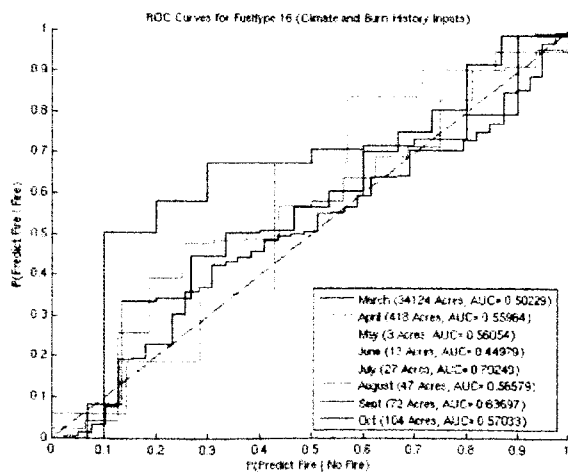
Fuel Code L: Western Perennial Grass (SVM method)



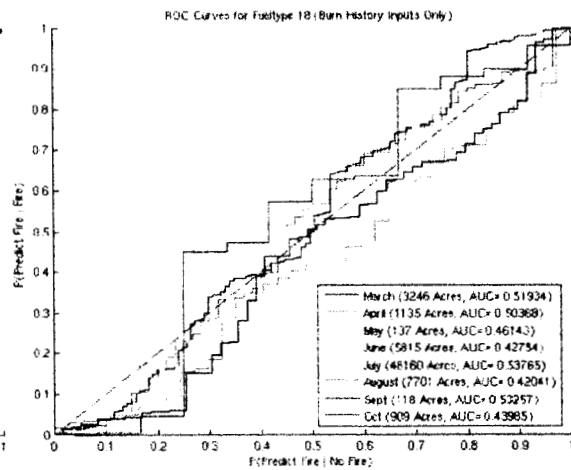
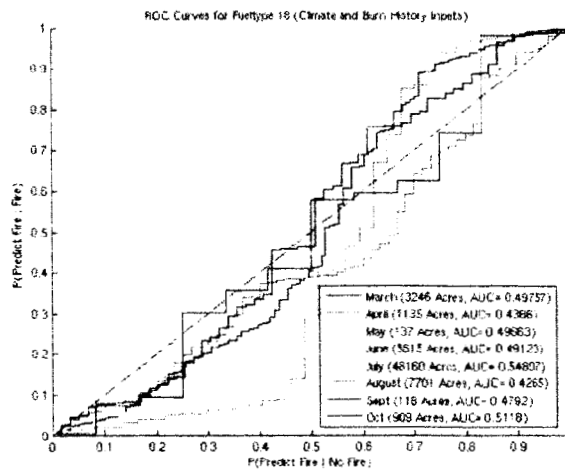
Fuel Code M: Agricultural Land (SVM method)



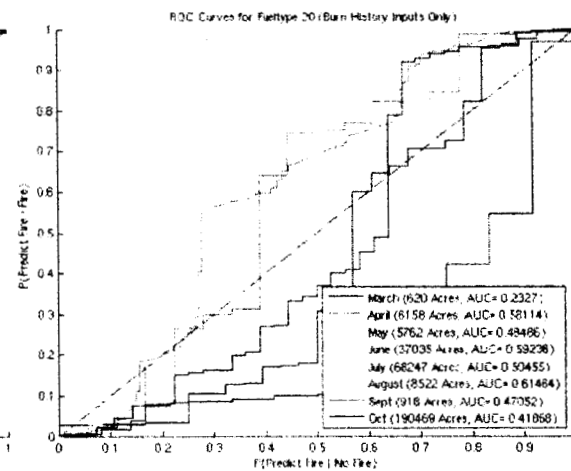
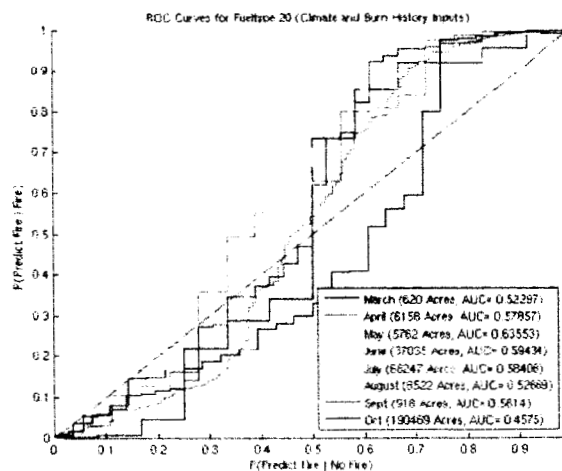
Fuel Code O: High Pocosin (SVM method)



Fuel Code P: Southern Pine Plantation (SVM method)



Fuel Code R: Hardwoods (SVM method)



Fuel Code T: Sagebrush-Grass Mixture (SVM method)

Appendix 2

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|------------------|------------------|--------------------------------|------------------|--------------------------------|--------------------------------|------------------|------------------|
| B | | | 0.862 0.835 | 0.68 0.7664 | 0.716 0.7964 | 0.732 0.736 | | 0.7587 0.7179 |
| C | 0.723 0.8235 | 0.7713 0.7493 | 0.825 0.7832 | 0.7565 0.7545 | 0.7513 0.7221 | 0.7279 0.7267 | 0.7944 0.8031 | 0.6544 0.7119 |
| F | | 0.7368 0.8115 | 0.6776 0.728 | 0.6757 0.7046 | 0.7773 0.7858 | 0.828 0.811 | 0.755 0.7599 | 0.837 0.7111 |
| G | | 0.7257 0.6258 | 0.6709 0.6775 | 0.7173 0.7269 | 0.6929 0.687 | 0.7022 0.6982 | 0.6313 0.6907 | 0.6816 0.7038 |
| H | | | 0.795 0.7783 | 0.6677 0.6716 | 0.6772 0.6687 | 0.716 0.7039 | 0.6307 0.7073 | 0.5155 0.5295 |
| L | | | 0.8438 0.8208 | 0.6894 0.7439 | 0.6128 0.6787 | 0.6948 0.6783 | 0.706 0.7537 | 0.6261 0.5832 |
| M | 0.6295 0.6509 | 0.7378 0.7806 | 0.6981 0.7368 | 0.722 0.7486 | 0.7662 0.7333 | 0.742 0.723 | 0.6925 0.7 | 0.7494 0.7618 |
| O | | 0.4184 0.5736 | 0.7671 0.8613 | | | | | |
| P | 0.5564 0.6025 | 0.5399 0.4809 | | | | | 0.5596 0.6438 | 0.6349 0.7293 |
| R | 0.7021 0.7278 | 0.5844 0.5652 | 0.8107 0.5862 | 0.7976 0.713 | 0.9282 0.6945 | 0.8487 0.6514 | 0.7237 0.7711 | 0.7051 0.7454 |
| T | 0.7342 0.8067 | 0.823 0.8484 | 0.726 0.7879 | 0.7235 0.7364 | 0.794 0.7621 | 0.7839 0.827 | 0.7216 0.7983 | 0.8241 0.762 |

Table 1: Logistic Regression, All Inputs vs. Logistic Regression, Burn History Inputs

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|
| B | | | 0.6618 0.4102 | 0.618 0.4234 | 0.6253 0.5549 | 0.6853 0.5284 | | 0.7355 0.5782 |
| C | 0.6559 0.4098 | 0.6565 0.5433 | 0.7231 0.6152 | 0.7322 0.6316 | 0.7328 0.642 | 0.6863 0.6045 | 0.7145 0.4869 | 0.6057 0.5186 |
| F | | 0.6164 0.6308 | 0.4998 0.5565 | 0.6067 0.6014 | 0.666 0.6243 | 0.6943 0.4919 | 0.4945 0.4617 | 0.4856 0.3251 |
| G | | 0.6503 0.5356 | 0.6049 0.5281 | 0.6704 0.6771 | 0.6486 0.6514 | 0.6436 0.6545 | 0.566 0.6269 | 0.6726 0.5182 |
| H | | | 0.6965 0.4012 | 0.605 0.5797 | 0.5888 0.5995 | 0.657 0.6109 | 0.5935 0.5814 | 0.4333 0.4797 |
| L | | | 0.5572 0.5425 | 0.6081 0.6187 | 0.5681 0.6192 | 0.5381 0.5902 | 0.6005 0.4686 | 0.3511 0.3108 |
| M | 0.6697 0.4632 | 0.3774 0.518 | 0.5873 0.454 | 0.6215 0.6463 | 0.604 0.5902 | 0.644 0.5255 | 0.7082 0.4217 | 0.4546 0.4726 |
| O | | 0.508 0.5628 | 0.7409 0.8174 | | | | | |
| P | 0.6026 0.548 | 0.554 0.661 | | | | | 0.3735 0.4263 | 0.7292 0.5258 |
| R | 0.5665 0.5589 | 0.4721 0.5591 | 0.3255 0.3846 | 0.5714 0.4832 | 0.8075 0.4651 | 0.6402 0.3871 | 0.4773 0.3702 | 0.5346 0.5417 |
| T | 0.6249 0.4521 | 0.6965 0.425 | 0.6716 0.6078 | 0.648 0.5976 | 0.6854 0.6511 | 0.7194 0.6726 | 0.7577 0.5531 | 0.6275 0.4944 |

Table 2: CART, All Inputs vs. CART, Burn History Inputs

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|--------------------------------|------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|-------------------------------|--------------------------------|
| B | | | 0.5763 0.5584 | 0.6504 0.5188 | 0.7154 0.5285 | 0.7059 0.4801 | | 0.5038 0.5993 |
| C | 0.4972 0.4729 | 0.5672 0.5884 | 0.6491 0.4684 | 0.6673 0.628 | 0.6685 0.5069 | 0.6523 0.4429 | 0.5948 0.5242 | 0.4646 0.5189 |
| F | | 0.5328 0.4879 | 0.579 0.5541 | 0.5839 0.6077 | 0.6398 0.5894 | 0.5162 0.545 | 0.5819 0.5558 | 0.4379 0.5403 |
| G | | 0.6453 0.5189 | 0.4816 0.537 | 0.5318 0.5163 | 0.5563 0.5772 | 0.5486 0.4932 | 0.4816 0.5114 | 0.5783 0.4064 |
| H | | | 0.4631 0.3189 | 0.4415 0.4918 | 0.5809 0.5259 | 0.5322 0.5056 | 0.5109 0.5542 | 0.4813 0.558 |
| L | | | 0.3204 0.6107 | 0.5219 0.5584 | 0.4869 0.4619 | 0.4341 0.4916 | 0.3481 0.4803 | 0.3201 0.4784 |
| M | 0.7101 0.4281 | 0.5182 0.5673 | 0.7013 0.571 | 0.6412 0.4604 | 0.6073 0.536 | 0.6299 0.44 | 0.5651 0.318 | 0.4225 0.5564 |
| O | | 0.3761 0.5845 | 0.5017 0.6461 | | | | | 0.0446 0.0382 |
| P | 0.5023 0.5683 | 0.5596 0.3751 | | | | | 0.637 0.4959 | 0.5783 0.3672 |
| R | 0.4976 0.5193 | 0.4366 0.5037 | 0.4966 0.4614 | 0.4912 0.4275 | 0.549 0.5376 | 0.4265 0.4204 | 0.4792 0.5326 | 0.5118 0.4399 |
| T | 0.523 0.2327 | 0.5786 0.5811 | 0.6355 0.4849 | 0.5943 0.5924 | 0.5841 0.5946 | | 0.5614 0.4705 | 0.4575 0.4187 |

Table 3: SVM, All Inputs vs. SVM, Burn History Inputs

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|
| B | | | 0.862 0.6618 | 0.68 0.618 | 0.716 0.6253 | 0.732 0.6853 | | 0.7587 0.7355 |
| C | 0.723 0.6559 | 0.7713 0.6565 | 0.825 0.7231 | 0.7565 0.7322 | 0.7513 0.7328 | 0.7279 0.6863 | 0.7944 0.7145 | 0.6544 0.6057 |
| F | | 0.7368 0.6164 | 0.6776 0.4998 | 0.6757 0.6067 | 0.7773 0.666 | 0.828 0.6943 | 0.755 0.4945 | 0.837 0.4856 |
| G | | 0.7257 0.6503 | 0.6709 0.6049 | 0.7173 0.6704 | 0.6929 0.6486 | 0.7022 0.6436 | 0.6313 0.566 | 0.6816 0.6726 |
| H | | | 0.795 0.6965 | 0.6677 0.605 | 0.6772 0.5888 | 0.716 0.657 | 0.6307 0.5935 | 0.5155 0.4333 |
| L | | | 0.8438 0.5572 | 0.6894 0.6081 | 0.6128 0.5681 | 0.6948 0.5381 | 0.706 0.6005 | 0.6261 0.3511 |
| M | 0.6295 0.6697 | 0.7378 0.3774 | 0.6981 0.5873 | 0.722 0.6215 | 0.7662 0.604 | 0.742 0.644 | 0.6925 0.7082 | 0.7494 0.4546 |
| O | | 0.4184 0.508 | 0.7671 0.7409 | | | | | |
| P | 0.5564 0.6026 | 0.5399 0.554 | | | | | 0.5596 0.3735 | 0.6349 0.7292 |
| R | 0.7021 0.5685 | 0.5844 0.4721 | 0.8107 0.3255 | 0.7976 0.5714 | 0.9282 0.8075 | 0.8487 0.6402 | 0.7237 0.4773 | 0.7051 0.5346 |
| T | 0.7342 0.6249 | 0.823 0.6965 | 0.726 0.6716 | 0.7235 0.648 | 0.794 0.6854 | 0.7839 0.7194 | 0.7216 0.7577 | 0.8241 0.6275 |

Table 4: Logistic Regression, All Inputs vs. CART, All Inputs

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| B | | | 0.862 0.5763 | 0.68 0.6504 | 0.716 0.7154 | 0.732 0.7059 | | 0.7587 0.5038 |
| C | 0.7221 0.4972 | 0.7213 0.5672 | 0.823 0.6491 | 0.7565 0.6673 | 0.7513 0.6685 | 0.7279 0.6523 | 0.7944 0.5948 | 0.6544 0.4646 |
| F | | 0.7368 0.5328 | 0.6776 0.579 | 0.6757 0.5839 | 0.7773 0.6398 | 0.828 0.5162 | 0.755 0.5819 | 0.837 0.4379 |
| G | | 0.7257 0.6453 | 0.6709 0.4816 | 0.7173 0.5318 | 0.6929 0.5563 | 0.7022 0.5486 | 0.6313 0.4816 | 0.6816 0.3783 |
| H | | | 0.795 0.4631 | 0.6677 0.4415 | 0.6772 0.5809 | 0.718 0.5322 | 0.6387 0.5109 | 0.5155 0.4813 |
| L | | | 0.8438 0.3204 | 0.6894 0.5219 | 0.6128 0.4869 | 0.6948 0.4341 | 0.706 0.3481 | 0.6261 0.3201 |
| M | 0.6295 0.7101 | 0.7378 0.5182 | 0.6981 0.7013 | 0.722 0.6412 | 0.7662 0.6073 | 0.742 0.6299 | 0.6925 0.5651 | 0.7494 0.4225 |
| O | | 0.4184 0.3761 | 0.7671 0.5017 | | | | | |
| P | 0.5564 0.5023 | 0.5399 0.5596 | | | | | 0.5596 0.637 | 0.6349 0.5703 |
| R | 0.7021 0.4976 | 0.5844 0.4366 | 0.8107 0.4966 | 0.7976 0.4912 | 0.9282 0.549 | 0.8487 0.4265 | 0.7237 0.4792 | 0.7051 0.5118 |
| T | 0.7342 0.523 | 0.823 0.5786 | 0.726 0.6355 | 0.7235 0.5943 | 0.794 0.5841 | 0.7839 0.5267 | 0.7216 0.5614 | 0.8241 0.4575 |

Table 5: Logistic Regression, All Inputs vs. SVM, All Inputs

| Fuel Code | March | April | May | June | July | Aug | Sept | Oct |
|-----------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| B | | | 0.6618 0.5763 | 0.618 0.6504 | 0.6253 0.7154 | 0.6853 0.7059 | | 0.7355 0.5038 |
| C | 0.6559 0.4972 | 0.6565 0.5672 | 0.7231 0.6491 | 0.7322 0.6673 | 0.7328 0.6685 | 0.6863 0.6523 | 0.7145 0.5948 | 0.6057 0.4646 |
| F | | 0.6164 0.5328 | 0.4998 0.579 | 0.6067 0.5839 | 0.666 0.6398 | 0.6943 0.5162 | 0.4945 0.5819 | 0.4856 0.4379 |
| G | | 0.6503 0.6453 | 0.6849 0.4816 | 0.6704 0.5318 | 0.6486 0.5563 | 0.6436 0.5486 | 0.566 0.4816 | 0.6726 0.5783 |
| H | | | 0.6965 0.4631 | 0.605 0.4415 | 0.5888 0.5809 | 0.657 0.5322 | 0.5935 0.5109 | 0.4333 0.4813 |
| L | | | 0.5572 0.3204 | 0.6081 0.5219 | 0.5681 0.4869 | 0.5381 0.4341 | 0.6005 0.3481 | 0.3511 0.3201 |
| M | 0.6697 0.7101 | 0.3774 0.5182 | 0.5873 0.7013 | 0.6215 0.6412 | 0.604 0.6073 | 0.644 0.6299 | 0.7082 0.5651 | 0.4546 0.4225 |
| O | | 0.508 0.3761 | 0.7409 0.5017 | | | | | |
| P | 0.6026 0.5023 | 0.554 0.5596 | | | | | | 0.7292 0.5703 |
| R | 0.5665 0.4976 | 0.4721 0.4366 | | 0.5714 0.4912 | 0.8075 0.549 | 0.6402 0.4265 | 0.4773 0.4792 | 0.5346 0.5118 |
| T | 0.6249 0.523 | 0.6965 0.5786 | 0.6716 0.6355 | 0.648 0.5943 | 0.6854 0.5841 | 0.7194 0.5267 | 0.7577 0.5614 | 0.6275 0.4575 |

Table 6: CART, All Inputs vs. SVM, All Inputs